

Structural Health Monitoring Using Statistical Pattern Recognition Techniques

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This paper casts structural health monitoring in the context of a statistical pattern recognition paradigm. Two pattern recognition techniques based on time series analysis are applied to fiber optic strain gauge data obtained from two different structural conditions of a surface-effect fast patrol boat. The first technique is based on a two-stage time series analysis combining Auto-Regressive (AR) and Auto-Regressive with eXogenous inputs (ARX) prediction models. The second technique employs an outlier analysis with the Mahalanobis distance measure. The main objective is to extract features and construct a statistical model that distinguishes the signals recorded under the different structural conditions of the boat. These two techniques were successfully applied to the patrol boat data clearly distinguishing data sets obtained from different structural conditions.

1. Introduction

Many aerospace, civil, and mechanical engineering systems continue to be used despite aging and the associated potential for damage accumulation. Therefore, the ability to monitor the structural health of these systems is becoming increasingly important from both economic and life-safety viewpoints. Damage identification based upon changes in dynamic response is one of the few methods that monitor changes in the structure on a global basis. The basic premise of vibration-based damage detection is that changes in the physical properties, such as reductions in stiffness resulting from the onset of cracks or loosening of a connection, will cause changes in the measured dynamic response of the structure.

Doebbling et al. (1998) present a recent thorough review of the vibration-based damage identification methods. While the references cited in this review propose many different methods for identifying and localizing damage from vibration response measurements, the majority of the cited references rely on finite element modeling process and/or linear modal properties for damage diagnosis. For practical applications, these methods have not been shown to be effective in detecting damage at an early state. To avoid the shortcomings of the methods summarized in this review, the authors have been tackling the damage detection problems based exclusively on the statistical analysis of measured test data.

This paper begins by posing the structural health-monitoring problem in the context of a statistical pattern recognition paradigm. This paradigm can be described as a four-part process: (1) operational evaluation, (2) data acquisition & cleansing, (3) feature extraction & data reduction, and (4) statistical model development. In particular, this paper focuses on Parts 3 and 4 of the process. More detailed discussion of the statistical pattern recognition paradigm can be found in Farrar et al, 2000.

It should be noted that neither sophisticated finite element models nor the traditional modal parameters are employed in the implementation of the statistical pattern recognition techniques because

the finite modeling and modal analysis often require labor intensive tuning and result in significant uncertainties caused by user interaction and modeling errors. The statistical approaches presented here are solely based on signal analysis of the measured vibration data making this approach very attractive for the development of an automated health monitoring system. Other statistical pattern recognition techniques also have been applied to various damage identification problems by the authors (Sohn et al., 2001a and 2001b; Worden et al., 1997 and 2000; and Fugate et al., 2001).

This paper is organized as follows: First, a novel time series technique is developed to identify damage or structural changes in a mechanical system, which is running in various operational and environmental conditions. Second, an outlier analysis using the Mahalanobis distance measure is applied to the AR coefficients extracted from the measured data in order to detect any abnormal changes of the system. Finally, the applicability of the proposed pattern recognition techniques has been demonstrated using the strain time histories obtained from two different structural conditions of a surface-effect fast patrol boat.

2. Description of Experimental Data

Staff at Los Alamos National Laboratory (LANL) applied some of the LANL pattern recognition techniques developed for structural health monitoring to data obtained from a surface-effect fast patrol boat shown in Figure 1. The surface effect ship is a pre-series fast patrol boat built by Kvaerner Mandal in Norway. Together with a research team from the Norwegian Defense Research Establishment (NDRE), the ship designers determined the optimal sensor placement. The sensor installation and data acquisition during sea trials was performed jointly by NDRE and Naval Research Laboratory (NRL). Therefore, the number, type and locations of sensors along with the data acquisition, storage, transmittal hardware and data sampling parameters were all established by NDRE and NRL. Fiber

optic strain gauges with Bragg grating were used to measure the dynamic response of the ship. The boat and the associated data acquisition are summarized in Wang and Pran (2000) and Johnson et al. (2000).

Three strain time-histories obtained from two different structural conditions were transmitted to the staff at Los Alamos National Laboratory (LANL) from NRL (see Figure 2). Each time history is recorded for 601.17 seconds and consists of 26980 time points, resulting in a sampling interval of 0.02228 seconds or a sampling rate of 44.88Hz. It was explained that the first two signals, Signal 1 and Signal 2, hereafter, were measured when the ship was in “Structural Condition 1” while Signal 3 was measured when the ship was in “Structural Condition 2”. However, it was not told which sensor these data came from. LANL staff was not informed of any data cleansing or signal processing that was performed prior to the transmission of these signals to LANL. It is assumed that these data were acquired under varying environmental and operational conditions. Changing environmental conditions can include varying sea states and thermal environments associated with the water and air. Changing operational conditions can include ship speed and the corresponding changes in engine performance, mass associated with varying ship cargo, ice buildup and fuel levels, and maneuvers the ship undergoes. No measures of these environmental or operational conditions were provided.

Given that the first two portions of the statistical pattern recognition paradigm (operational evaluation and data acquisition & data cleansing) have mostly been completed, this study focused on data normalization, feature extraction, and statistical modeling for feature discrimination. Here, data normalization is a procedure to “normalize” data sets such that signal changes caused by operational and environmental variations of the system can be separated from structural changes of interests (for example, structural deterioration or degradation). The goal of this investigation is to normalize these data and extract the appropriate features such that Signal 3 could be clearly discriminated from Signals

1 and 2. Also, it must be shown that the same procedure does not discriminate Signal 1 from Signal 2. The following section describes various procedures attempted to obtain these goals.

3. Statistical Pattern Recognition Techniques

Preliminary Analyses. First, the raw time series are plotted in Figure 2 to get some intuitive feeling for the signals. A few observations could be made based on this figure: (1) All the signals have “spiky” responses with an occasional large amplitude strain measurement, (2) the amplitude of one signal is not consistent with the amplitude of the other signals indicating the need for data normalization, and (3) significant “skewness” is found in Signal 2. To support some of these observations, the first four moment statistics of the raw time series are summarized in Table 1. A close look of Table 1 further reveals important facts regarding the data. The sample mean and standard deviation (STD) of one time series are quite different from those of the others signals. Particularly, it is speculated that because the boat was cruising at a high speed when Signal 2 was recorded, the boat was making intermitted contacts with the sea surface resulting in large amplitudes in one directional response. (That is, a large skewness value is observed for Signal 2.) Therefore, it seems necessary to conduct some form of data normalization or standardization prior to any statistical model development.

To achieve the main objective, which is to group Signals 1 and 2 together and to separate Signal 3 from Signals 1 and 2, various signal analyses have been conducted. To name a few, Fast Fourier Transformation (FFT) analysis, Principal Component Analysis on the first four moment statistics, Statistical Control Chart Analysis using residual errors obtained from AR models, Probability Density Estimation of the residual errors, Bispectrum & Bicoherence Analysis, and Time-Frequency Analysis using Spectrogram. However, it was difficult to discern, either qualitatively or quantitatively, any consistent difference between Signals 1 and 2 (Structural Condition 1) and Signal 3 (Structural

Condition 2) and at the same time group Signals 1 and 2 together. The visual inspection of some results often shows more similarity between Signals 1 and 3 than between Signals 1 and 2. The conclusion from the aforementioned analyses was that environmental conditions such as sea states or operational conditions such as the boat speed were making it impossible to distinguish between the two structural states. The details of these analyses are summarized in Sohn et al., 2001c.

AR-ARX Analysis. As mentioned in the previous subsection, there is a noticeable difference between Signals 1 and 2 because of operational variation of the boat. It seems extremely difficult to group Signals 1 and 2 together, and at the same time separate Signal 3 from them. For real world structures, it quickly becomes apparent that the ability to normalize data in an effort to account for operational and environmental variability is a key implementation issue when addressing feature extraction and statistical modeling parts of the statistical pattern recognition paradigm. These strategies for SHM data normalization fall into two general classes: (1) those employed when measures of the varying environmental and operational parameters are available, and (2) those employed when such measures are not available. A primary focus of this study is to develop a data normalization procedure that can be employed for Case (2) when measures of the varying environmental and operational conditions are not available.

First, the data normalization procedure here begins by assuming that a “pool” of signals is acquired from various unknown operational and environmental conditions, but from a known structural condition of the system. The ability of this procedure to normalize the data will be directly dependent on this pool being representative of data measured in as many varying environmental and operational conditions as possible. The collection of these time series is called “the reference database” in this study.

For this particular example at hand, each signal is first divided into two parts. The first halves of Signal 1 and Signal 2 are employed to generate the “reference database”. The second halves of Signal 1 and Signal 2 are later employed for false-positive studies. In this example, signal “blocks” in the reference database are generated by further dividing the first halves of Signal 1 and Signal 2 into smaller segments. These reference signals are considered to be “the pool” of signals acquired from the various operational conditions, but from a known structural condition of the system. (In this example, Signals 1 and 2 are assumed to have been measured under different operational conditions of the surface-effect fast patrol boat. However, it is also known that these two signals correspond to the same structural condition of the system.) When a new signal is recorded (for example, when Signal 3 is measured), this signal is divided into smaller segments, as done for the blocks in the reference database. Then, the signals in the reference database are examined to find a signal block “closest” to the new signal block, and the selected signal is designated a “reference signal”. Here, the metric, which is defined as the distance measure of two separate signal segments, is subjective. The detailed formulation of the metric used in this study and the definition of the “closeness” will be described later on.

Second, a two-stage prediction model, combining Auto-Regressive (AR) and Auto-Regressive with eXogenous inputs (ARX) techniques, is constructed from the selected reference signal. Then, the residual error, which is the difference between the actual acceleration measurement for the new signal and the prediction obtained from the AR-ARX model developed from the reference signal, is defined as the damage-sensitive feature.

This approach is based on the premise that if the new signal block is obtained from the same operational condition as one of the reference signal segments and there has been no structural deterioration or change to the system, the dynamic characteristics of the new signal should be similar to

those of the reference signal based on some measure of “similarity”. That is, if a time prediction model, such as AR-ARX model employed here, is constructed from the selected reference waveform, this prediction model also should work for the new signal if the signal is “close” to the original.

For example, if the second half of Signal 1 is assumed to be a new blind-test signal, the prediction model obtained from the first half of Signal 1 should reproduce the new signal (the second half of Signal 1) reasonably well. (Here, we are assuming that the structural condition did not change throughout the acquisition of Signal 1.) On the other hand, if the new signal is recorded under a structural condition different from the conditions where reference signals are obtained, the prediction model estimated from even the “closest” waveform in the reference database should not predict the new signal well. For instance, because Signal 3 is measured under the different structural condition of the system, the prediction model obtained from either Signal 1 or Signal 2 would not predict Signal 3 well even if “similar” waveforms were analyzed. Therefore, the residual errors of the “similar” signals are defined as the damage-sensitive features, and the change of the probability distribution of these residual errors is monitored to detect system anomaly. The procedure is described below in detail.

- 1 All three signals are decimated by a factor of four. This decimation reduces the original sampling rate of the signal, 44.88Hz, to a lower rate, 11.22Hz. The decimation process first filters the signal with an eighth-order lowpass Chebyshev type I filter for better anti-aliasing performance. (The cutoff frequency is set to be $(0.8/R) \times (F_s / 2)$. Here, F_s is the original sampling rate, 44.88Hz, and R is the decimation rate, 4.) Then, the decimation process re-samples the resulting filtered signal at the lower rate of 11.22Hz (Oppenheim and Willsky, 1996). Each signal consists of 26980 points with the duration of 601.1667 seconds and resulting in a sampling rate of 44.88Hz ($=26980/601.1667\text{Hz}$). This sampling rate corresponds to the Nyquist frequency of 22.44Hz.

Because the response is mainly observed in the frequency range of 0–5Hz, the signal is re-sampled at every fourth point resulting in the Nyquist frequency of 5.61Hz.

- 2 Next, an individual signal is divided into two parts. The first halves of Signal 1 and Signal 2 are employed to generate the reference database. Because each signal consists of 6745 ($=26980/4$) points after decimation, the first half of the signal is now composed of 3372 points. This 3372 point signal is further divided into smaller overlapping segments. The length of a single segment is set to be 1148. (The selection of this segment length is described later.) Therefore, 2225 ($=3372-1148+1$) overlapping segments are generated from the first half of Signal 1 using a moving time window with 1148 time points. In a similar manner, 2225 segments are obtained from the first half of Signal 2. Therefore, the reference database consists of a total of 4450 signal blocks.
- 3 Signal 3 is divided into two parts in the same fashion as in Step 2, and either the first or second half of Signal 3 is assumed as a new data set. In this example, the whole procedure is demonstrated using the second half of Signal 3. The second half of Signal 3 is further divided into three segments. Note that each segment has the same length of 1148 time points as all the reference signal blocks.
- 4 For each segment of the new data, the reference signals are looked up and the signal segment that is “closest” to the newly obtained one is found. This procedure can be interpreted as a normalization procedure that finds a reference signal segment recorded under a similar “operational” or “environmental” condition as the newly measured one. The “closeness” between two blocks is measured in the following manner.

4.1 For each segment $x(t)$ from the reference database, construct an AR model with p autoregressive terms. An AR(p) model can be written as:

$$x(t) = \sum_{j=1}^p \phi_{xj} x(t-j) + e_x(t) \quad (1)$$

This step is repeated for all 4450 segments in the reference database. In this example, the AR order is set to be 30 based on a partial auto-correlation analysis described in Box et al. (1994).

4.2 Employing a new segment $y(t)$ obtained from the second half of Signal 3, repeat Step 4.1 Here, segment $y(t)$ has the same length as segment $x(t)$:

$$y(t) = \sum_{j=1}^p \phi_{yj} y(t-j) + e_y(t) \quad (2)$$

Then, the signal segment $x(t)$ closest to the new signal block $y(t)$ is defined as the one that minimizes the difference of AR coefficients:

$$\text{Difference} = \sum_{j=1}^p (\phi_{xj} - \phi_{yj})^2 \quad (3)$$

This “data normalization” is a procedure to select the previously recorded time signal from the reference database, which is recorded under operation and/or environmental conditions closest to that of the newly obtained signal. If the new signal block is obtained from an operational condition close to one of the reference signal segments and there has been no structural deterioration or damage to the system, the dynamic characteristics (in this case, the AR coefficients) of the new signal should be similar or “closest” to those of the reference signal based on the Euclidean distance measure in Equation (3).

- 5 It was assumed that the strain measurements are significantly affected by varying sea states. Therefore, it is necessary to separate the changes in the system response caused by the varying

structural conditions from changes caused by varying sea state. It is assumed that the error between the measurement and the prediction obtained by the AR model ($e_x(t)$ in Equation (1)) is mainly caused by the unknown external input. Based on this assumption, an ARX model (Auto-Regressive model with eXogenous inputs) is employed to reconstruct the input/output relationship between $e_x(t)$ and $x(t)$. That is, considering the error term $e_x(t)$ an exogenous input to the system, an ARX(a,b) model is fit to the data to capture the input/output relationship between $e_x(t)$ and $x(t)$. The ARX model is defined as:

$$x(t) = \sum_{i=1}^a \alpha_i x(t-i) + \sum_{j=0}^b \beta_j e_x(t-j) + \varepsilon_x(t) \quad (4)$$

where $\varepsilon_x(t)$ is the residual error after fitting the ARX(a,b) model to the $e_x(t)$ and $x(t)$ pair. The feature for the classification of damage status will later be related to this quantity, $\varepsilon_x(t)$. Note that this AR-ARX modeling is similar to a linear approximation method of an Auto-Regressive Moving-Average (ARMA) model presented in Ljung 1987 and references therein. Ljung (1987) suggested to keep the sum of a and b smaller than p ($a + b \leq p$). ARX(5,5) is used in this example. Here, the a and b values of the ARX model are set rather arbitrarily. However, similar results are obtained for different combinations of a and b values as long as the sum of a and b is kept smaller than p ($a + b \leq p$).

- 6 Next, an investigation is made to determine how well the ARX(a,b) model estimated in Equation (4) reproduces the input/output relationship of $e_y(t)$ and $y(t)$:

$$\varepsilon_y(t) = y(t) - \sum_{i=1}^a \alpha_i y(t-i) - \sum_{j=0}^b \beta_j e_y(t-j) \quad (5)$$

where $e_y(t)$ is considered to be an approximation of the system input estimated from Equation (2). Again, note that the α_i and β_j coefficients are associated with $x(t)$ and obtained from Equation (4). Therefore, if the ARX model obtained from the reference signal block $x(t)$ was not a good representative of the newly obtained signal segment $y(t)$ and $e_y(t)$ pair, there would be a significant change in the probability distribution of the residual error, $\varepsilon_y(t)$.

- 7 Finally the ratio of $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ is defined as the damage-sensitive feature in this particular example. Here, $\sigma(\varepsilon_y)$ and $\sigma(\varepsilon_x)$ are the estimated standard deviations of $\varepsilon_y(t)$ and $\varepsilon_x(t)$, respectively. If the ratio of $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ becomes larger than some threshold value $h (>1)$;

$$\frac{\sigma(\varepsilon_y)}{\sigma(\varepsilon_x)} > h \quad (6)$$

The system is considered to have undergone some structural system changes. However, in order to establish the threshold value, test data need to be acquired under different operational conditions, and the probability distribution of $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ first needs to be estimated. Because the data sets provided are limited, the construction of the threshold value based on a rigorous statistical analysis is not achieved in this study. Various studies based on hypothesis testing and Monte Carlo Simulation (Box and Andersen 1955, Miller 1997, and references therein) could be potentially employed to check if the new signal has significantly changed from the closest signal selected from the reference database.

This AR-ARX is also applied to locate damage sources assuming that the increase in residual errors would be maximized at the sensors instrumented near the actual damage locations. The

applicability of this approach is successfully demonstrated using acceleration time histories obtained from an eight degrees-of-freedom (DOFs) mass-spring system (Sohn and Farrar, 2001b).

Outlier Analysis. Outlier analysis and removal has long been a concern of statisticians and the subject has a large literature, the standard reference though, is Barnett and Lewis (1994). Here, only the briefest survey is given for the sake of completeness. A detailed study of direct relevance to structural health and condition monitoring can be found in Worden, et al (2000).

A *discordant outlier* in a data set is an observation that is surprisingly different from the rest of the data, and therefore is believed to be generated by an alternative mechanism. The discordance of the candidate outlier is a measure, which may be compared against some objective criterion. This measure allows the outlier to be judged to be statistically likely or unlikely to have come from an assumed generating model. For damage detection purposes, the generating model is simply the normal condition features of the machine or structure.

The case of outlier detection in univariate data is relatively straightforward in that outliers must “stick out” from one end or the other of the data set distribution. There are numerous discordance tests but one of the most common, and the one whose extension to multivariate data will be employed later, is based on deviation statistics and given by

$$z_{\xi} = \frac{x_{\xi} - \bar{x}}{s} \quad (7)$$

where x_{ξ} is the potential outlier, and \bar{x} and s are the sample mean and standard deviation, respectively. The latter two values may be calculated with or without the potential outlier in the sample depending

upon whether *inclusive* or *exclusive* measures are preferred. This discordance value is then compared to some threshold value and to determine if the observation is an outlier¹.

In general, a multivariate data set consisting of n observations in p variables may be represented as n points in p -dimensional object space. It becomes clear that detection of outliers in multivariate data is more difficult than in the univariate case due to the potential outlier having more room to hide.

The discordance test, which is the multivariate equivalent of Equation (7), is the Mahalanobis squared distance measure given by,

$$D_{\xi} = (\mathbf{x}_{\xi} - \bar{\mathbf{x}})^T \mathbf{s}^{-1} (\mathbf{x}_{\xi} - \bar{\mathbf{x}}) \quad (8)$$

where \mathbf{x}_{ξ} is the potential outlier vector, $\bar{\mathbf{x}}$ is the mean vector of the sample observations and \mathbf{s} the sample covariance matrix.

As with the univariate discordance test, the mean and covariance may be inclusive or exclusive measures. In many practical situations the outlier is not known beforehand and so the test would necessarily be conducted inclusively. In the case of on-line damage detection the potential outlier is, however, always known beforehand. (It is simply the most recent sampled point). Therefore, it is more sensible to calculate a value for the Mahalanobis squared distance without this observation contaminating the statistics of the normal data. Whichever method is used, the Mahalanobis squared distance of the potential outlier is checked against a threshold value, as in the univariate case, and its status determined.

Determination of the rejection threshold is critical. This value is dependent on both the number of observations and the dimension of feature space being selected. A Monte Carlo method was used here

¹Here outlier detection is used synonymously with novelty detection. The idea is to associate a new state of the system with the outliers. This use is distinguished from other uses of the outlier analysis in statistics, where the outlier may simply result from a fault in the data capture and be removed in order that it not bias any statistics estimated on the other data.

to arrive at the threshold value. The procedure for this method was to construct a $p \times n$ (dimension of feature space \times number of observations) matrix with each element being a randomly generated number from a normal distribution with zero mean and a unit variance. The Mahalanobis squared distances were calculated for all the p -vector components, using Equation (8) where $\bar{\mathbf{x}}$ and \mathbf{s} are inclusive measures, and the largest value stored. This process was repeated for at least 1000 trials whereupon the array containing all the largest Mahalanobis squared distances was then ordered in terms of magnitude. The critical values for the 5% and 1% tests of discordance are given by the Mahalanobis squared distances in the array above which 5% and 1% of the trials occur. This process is rather time-consuming and even more so if an exclusive threshold is required, fortunately a simple formula is available which converts inclusive to exclusive thresholds and vice-versa (Barnett and Lewis, 1994).

Note that there is an implicit assumption throughout that the normal condition set has a Gaussian distribution. This assumption will not generally be true. However, if the deviations from the normality are small, i.e. the true distribution is uni-modal and has appropriately weighted tails, the outlier analysis may work very well. If the normal condition set is multi-modal or deviates significantly from a Gaussian distribution, other methods should be used. Possible alternatives include density estimates (Bishop, 1995 and Tarassenko, 1995) or auto-associative networks (Pomerleau, 1993, and Worden, 1997).

4. Application to the Data of Surface-Effect Fast Patrol Boat

Results of AR-ARX analysis. The first example is conducted using the first half segments of Signals 1 and 2 as the reference database. Here, the first half of Signal 3 and the second half segments of Signals 1, 2 and 3 are employed as four testing segments with 3372 time points. Figure 3 shows the measured time series of the four testing segments and the corresponding prediction estimated using the

ARX (5,5) models as prescribed in the previous subsection. In Figure 3, the responses in the range of 100–120 seconds are enlarged for better comparison. If the system has experienced a change in structural condition, the standard deviation of new data, $\sigma(\varepsilon_y)$ defined in Equation (6), is expected to increase compared to the standard deviation of the reference signal, $\sigma(\varepsilon_x)$. For example, as shown in the first row of Table 2, $\sigma(\varepsilon_y)$ of the second half of Signal 1 increased about 57% from that of the selected reference signal blocks. (As mentioned earlier, each testing time series consist of 3372 points and they are further divided into 3 segments with 1148 points. $\sigma(\varepsilon_y)$ and $\sigma(\varepsilon_x)$ are computed based on all the residuals obtained from these three segments.)

A smaller increase in standard deviation, 26%, is observed for the second half of Signal 2. However, as expected, the standard deviations of the first or second halves of Signal 3 significantly differ from those of the selected reference signals. The standard deviations of the residual errors increased by 126% and 128%, for the first and second halves of Signal 3, respectively. A similar analysis, using the second half segments of Signals 1 and 2 as the reference signals, is presented in the second row of Table 2. In this second example, the first half segments of Signals 1, 2, and 3, and the second half of Signal 3 are employed as testing data sets. Again, a larger value in the $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ ratio is found for the residuals from Signal 3 than those from either Signal 1 or Signal 2.

Third, similar tests are repeated 20 times by randomly drawing testing signal blocks from Signals 1, 2 and 3. For the first 10 random tests, the first halves of Signals 1 and 2 are used as the reference signals, and 10 testing signal blocks are sampled from each of the first half of Signal 3 and the second half segments of Signals 1, 2 and 3. That is, 4 signal blocks are sampled from Signals 1, 2, and 3 for an individual test. Each signal block consists with 1148 time points as done in the previous examples. Testing blocks for the next 10 tests are collected from the first halves of Signal 1, 2 and 3, and the second half of Signal 3 because the second halves of Signals 1 and 2 are used as the reference signals.

To summarize, 20 blocks are sampled from either the first or second half of Signal 1 depending on which portion of Signal 1 is used as part of the reference database. In a similar way, 20 blocks are drawn from Signal 2. Additional 40 blocks are collected from Signal 3 (20 from the first half and another 20 from the second half). The $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ ratios for these testing blocks are summarized in Table 3. On average, the 20 testing blocks sampled from Signal 1 have $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$ value of 1.5187. The average value for the 20 signals from Signal 2 is 1.4321. On the other hand, the 40 blocks sampled from Signal 3 have much larger increases in standard deviation. The average value is about 2.2808 ($= (2.1902+2.3713)/2$).

In Figure 4, separation of Signal 3 from Signals 1 and 2 is attempted by setting the threshold value in Equation (6) to be 1.85. This threshold value ($h=1.85$) results in only 4 misclassifications out of 80 tested cases. That is, 95% of the tested blocks are correctly assigned to their structural conditions. Note that the threshold value employed here is established rather in an *ad hoc* manner. When more test data become available, the threshold value should be established based on a more rigorous statistical approach. However, it was shown that Signal 3 is somehow different from either Signal 1 or Signal 2 employing the additional information that Signals 1 and 2 are obtained from the same structural condition. The same procedure also shows that Signals 1 and 2 are similar. The additional studies with randomly selected testing signals showed no false-positive indication of structural changes, and discriminate Signal 3 from Signals 1 and 2 with a 95% of success rate. It should be noted that the separation of the two structural conditions is conducted in a supervised learning mode because the construction of the threshold value requires the acquisition of data from both of structural conditions.

Results of Outlier Analysis. The 30-dimensional AR parameters defined in Equations (1) and (2) were used again for the outlier analysis. The training data was composed of half of Signal 1 and Signal

2. In order to compensate for the nonstationarity of the AR parameter sequence, the training data and testing data were taken alternately from the relevant feature sets. This sampling procedure means that the training data are sampled from the whole time range of the record. The testing data comprised the remaining features from Signals 1 and 2 together with all the features from Signal 3. The resulting outlier statistic is shown in Figure 5. The threshold is the 99.99% confidence threshold, any values above this threshold have a less than 0.01% probability of arising as a random fluctuation on the normal condition set. There is an extremely clear separation between Structural Condition 1 and Structural Condition 2, also note that all points in the testing set from Signals 1 and 2 are well below threshold implying no false-positive indication of changes in structural conditions.

5. Conclusions

A vibration-based damage detection problem is cast in the context of statistical pattern recognition. A paradigm of statistical pattern recognition is described in four parts: operational evaluation, data acquisition & cleansing, data reduction & feature extraction, and statistical modeling for discrimination. This study has focused on the issues of data normalization, feature extraction, and statistical model development. Three strain measurements obtained from a surface-effect fast patrol boat were studied in this paper. The structural condition was the same when Signals 1 and 2 were obtained but Signal 3 was recorded in a different structural condition than when Signals 1 and 2 were obtained.

Following the proposed AR-ARX technique and outlier analysis, this study successfully identifies features from the strain time histories that distinguish Signal 3 from Signals 1 and 2. The features employed in this study, the standard deviation ratio of the residual errors and the Mahalanobis distance of AR coefficient vectors, showed a clear distinction between Signal 3 and Signals 1 and 2. Also

Signals 1 and 2 appeared to be similar when compared through these features. However, it should be pointed out that the procedure developed has only been verified on a limited amount of data. Ideally, it would be necessary to examine many time records corresponding to a wide range of operational and environmental cases as well as different damage scenarios before one could state with confidence that the proposed method is robust enough to be used in practice.

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Figure 1: A surface-effect fast patrol boat

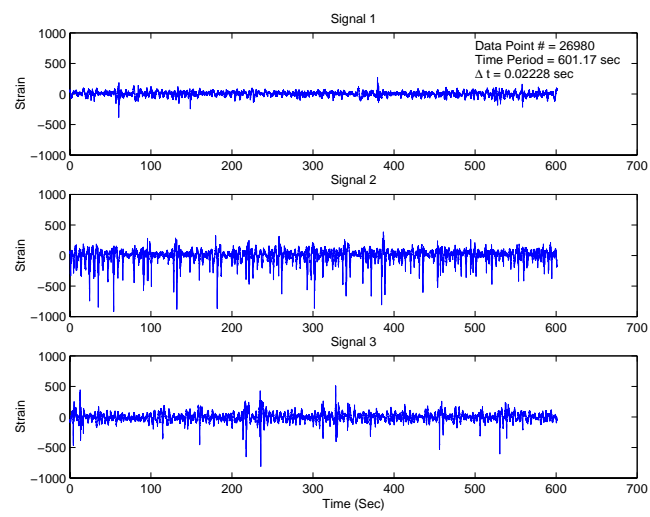


Figure 2: The raw strain time series

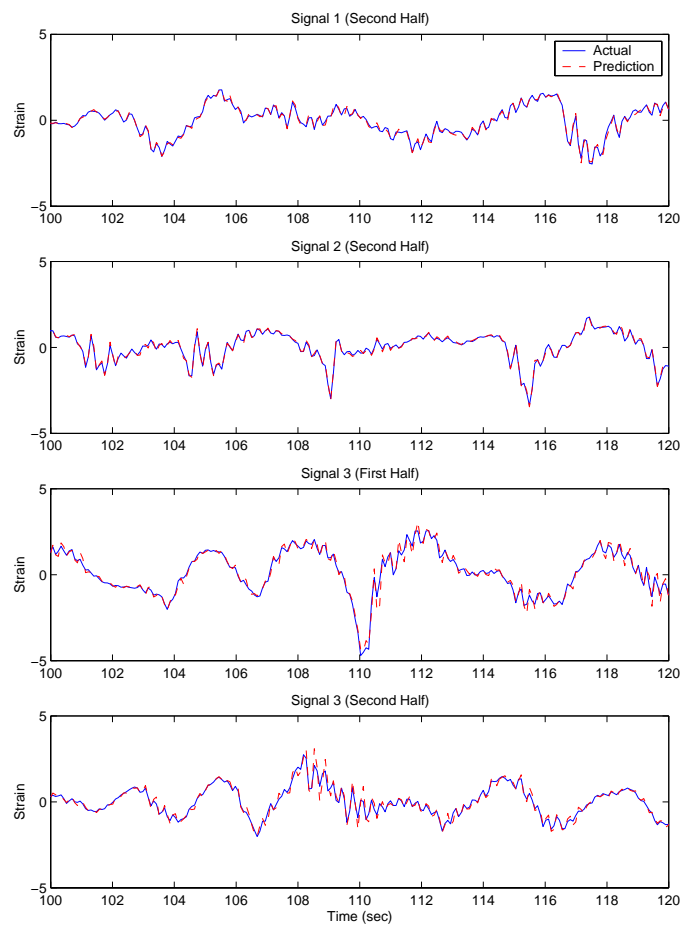


Figure 3: Comparison of the measured vs. predicted signals (zoomed)

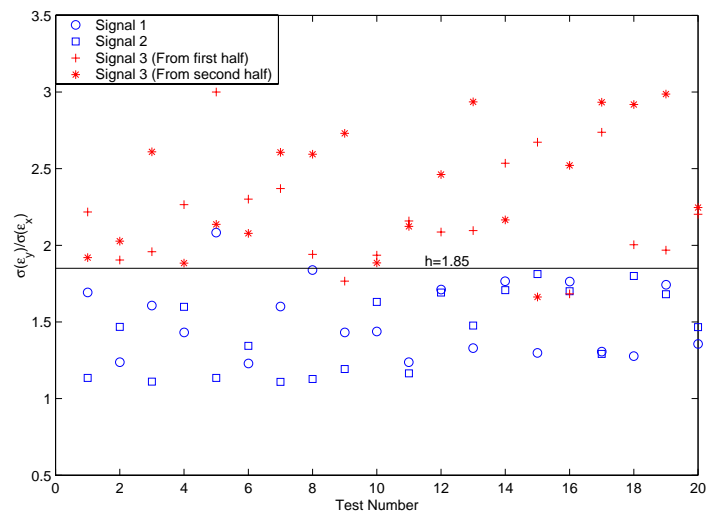


Figure 4: Separation of Signal 3 from Signals 1 and 2 using the ARX residual errors

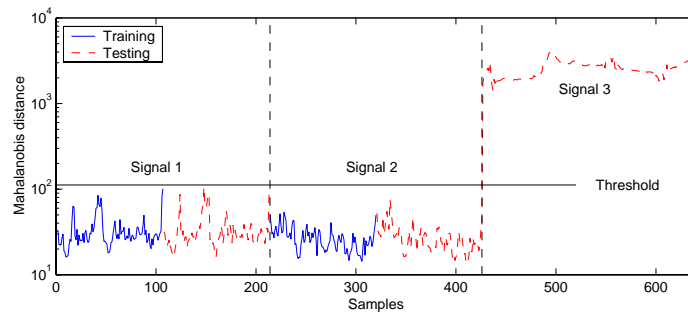


Figure 5: Outlier Statistics for Signals 1-3

Table 1: Basic statistics of the raw time series amplitudes

Series	Mean	STD	Skewness	Kurtosis
Signal 1	3.7809	37.7433	-0.4811	6.0854
Signal 2	-0.8207	107.8089	-2.2310	12.6311
Signal 3	-0.7559	74.1260	-0.8134	11.9437

Table 2: Extracted feature: standard deviation ratio of the residual errors

Feature	Signal 1		Signal 2		Signal 3	
	1st	2nd	1st	2nd	1st	2nd
$\sigma(\varepsilon_y)$	Ref. [†]	1.5667	Ref. [†]	1.2609	2.2625	2.2811
$\sigma(\varepsilon_x)$	1.5045	Ref. [†]	1.3995	Ref. [†]	2.6209	2.5827

[†]Signal segments with the “reference” notation are used as part of the reference database.

Table 3: The average ratio of standard deviations for randomly selected 20 signal blocks

Test #	$\sigma(\varepsilon_y) / \sigma(\varepsilon_x)$			
	Signal 1	Signal 2	1st half of Signal 3	2nd half of Signal 3
Mean	1.5187	1.4321	2.1902	2.3713